Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 47 (2012) 1069 – 1072

Procedia Engineering

www.elsevier.com/locate/procedia

Proc. Eurosensors XXVI, September 9-12, 2012, Kraków, Poland

An olfactory bulb model mitigates the drift in chemical sensors

D. Polese[a], E. Martinelli[a*], A. D'Amico[a], C. Di Natale[a]

[a]*Department of Electronic Engineering, University of Rome Tor Vergata, Rome, Italy*

Abstract

The observations of natural olfaction led to the evidence that the processing of olfactory receptor signals contributes to properties such as performance stability, concentration invariance, and background suppression. Then, the study of olfactory processing has been regarded as a valuable source of inspiration for sensor arrays. In this work, a neural network architecture, introduced in the past as a model of the olfactory bulb, is used as a pre-processing step to analyse the data of an array of chemical sensors. Surprisingly, besides to enforce gas recognition, the network shows an interesting property of drift rejection. The potentialities of the network are demonstrated with data collected in a long-time experiment. The results provide strong evidence that bio-inspired processing of chemical sensors data actively improve the overall performance.

Keywords: Bioinspired Algorithm, Chemical Sensor Drift, Olfactory Bulb Model

1. Introduction

The study of the olfactory bulb led to the design of a number of neural networks that could account for the many observed functionalities [1]. Among them the following are the most interesting for chemical sensors: the stability of performance (i.e the recognition capability does not change even if individual olfactory neuron signals fluctuate), the concentration invariance (i.e gases are recognized independently from their concentrations) [2], and fast recognition [3]. For these reasons, bio-inspired processing is regarded as an important source of inspiration for chemical sensors data analysis [4]. However, previous

* Corresponding author. Eugenio Martinelli, via del Politecnico 1, 00133 Roma Italy, Tel: +390672597259.
E-mail address: martinelli@ing.uniroma2.it.

doi:10.1016/j.proeng.2012.09.335

studies did not yet put into evidence that bio-inspired processing may outperform the standard multivariate statistics approach.

This paper considers an unsupervised neural network where the dendritic signal processing is performed by a network of mitral and periglomerular cells as it occurs in the olfactory bulb [5]. The multi-compartment modelling and the local learning rule of the network weights are the main features of the network algorithm that is designed in order to achieve the correct classification of different stimuli into well separated classes.

2. Results

Fig. 1 shows the processing steps of the sensor signals. For each sensor, the maximum shift of the response signal before and after the chemical stimulus application is the measurement descriptor. The network is used as a pre-processor before the application of a classifier. Here for sake of simplicity, a linear classifier such as Partial Least Square Discriminant Analysis (PLS-DA) has been considered. Then the test consists in the comparison of the PLS-DA prediction obtained with and without the network pre-processing.

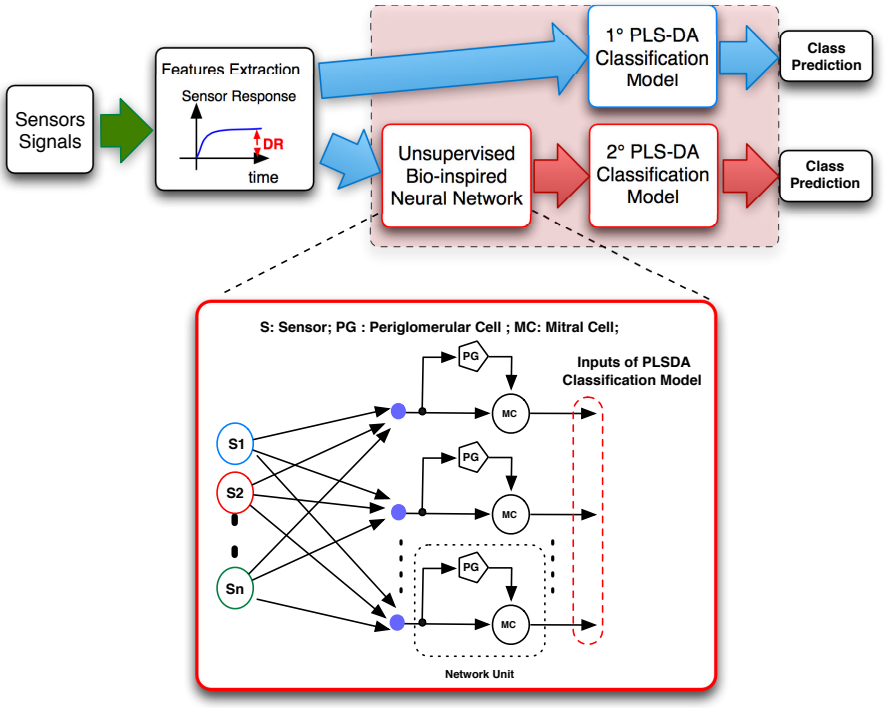

Fig. 1. Steps of the data processing. Pre-processed and non-pre-processed data are classified by a PLS-DA classifier. The architecture of the neural model is shown in the box.

The experimental dataset is related to an array of 16 commercial metal oxide gas sensors, composed of 4 replicas of 4 different sensors (TGS2600, TGS2602, TGS2610, TGS2620) exposed to five volatile

compounds (ammonia, acetaldehyde, acetone, ethylene, ethanol) presented to the same concentration (225 ppm in standard air). The experiments took 18 months during which 856 independent data were collected. During the experiment the sensors exhibited a non-negligible drift. The magnitude of the drift can be appreciated in Fig. 2 where the responses to the five compounds of one of the sensor of the array is shown. The first 100 measurements were used to train the network and the remaining 756 measures for test.

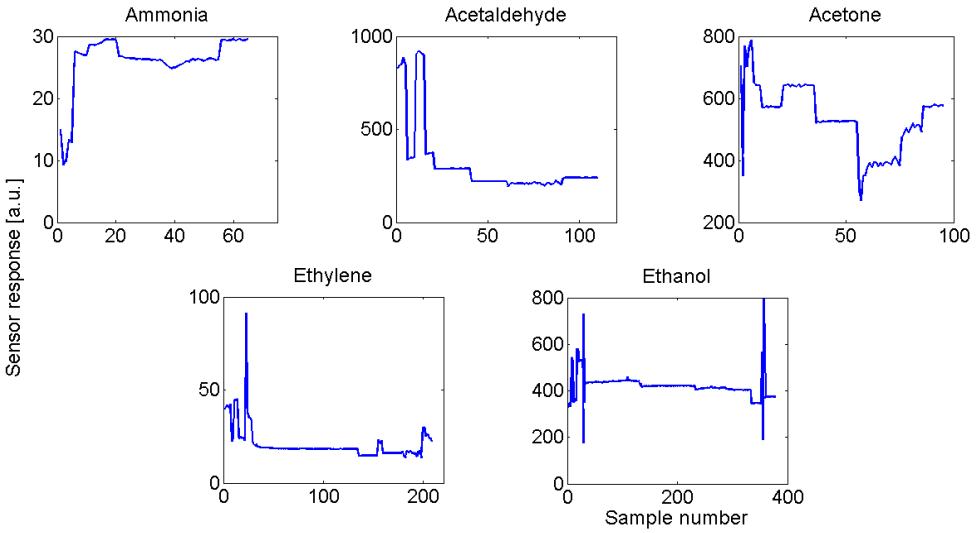

Fig. 2. Time sequence of the responses to the five compounds of one of the sensors of the array.

The training data were presented several times to the network. The output signals of the last training epoch were used as input of the PLS-DA classifier. Test data were presented only one time to the network and the outputs of the network were used again as input of the PLS-DA classifier.

The effects of the network pre-processing are evidenced comparing the classification rates of the models with pre-processed and non pre-processed data. Results show that the presence of the pre-processing network improves the classification rate from 77% to 96%. Table 1 shows the confusion matrices for the classifiers obtained with and without the pre-processing. According to the table, the network improves the classification rate of all the five compounds. Remarkable results are obtained for acetaldehyde (from 22% to 79%) and acetone (from 68% to 97%).

3. Conclusions

In conclusion, a pre-processing unit of sensor responses based on an unsupervised and bio-inspired neural network has been applied to a sensor array data. As a result, the gas recognition as carried out by a linear classifier strongly improves. Since the major limitation to recognition is the drift of sensor signals, we can conclude that the bio-inspired network has the effect of reducing the drift of the sensors. These results can be mainly ascribed to the continuous learning of the network weights whose plasticity can follow the drifting sensor responses.

Table 1. Top: confusion matrix of the PLS-DA model without pre-processing. Bottom: confusion matrix of the PLS-DA model obtained from pre-processed data.

		Predicted				
		Ammonia	Acetaldet.	Acetone	Ethylene	Ethanol
Measured	Ammonia	**45**	0	0	0	0
	Acetaldet.	**30**	**20**	**2**	0	**38**
	Acetone	0	**24**	**51**	0	0
	Ethylene	**30**	0	**40**	**118**	0
	Ethanol	0	**6**	0	0	**352**

		Predicted				
		Ammonia	Acetaldet.	Acetone	Ethylene	Ethanol
Measured	Ammonia	**45**	0	0	0	0
	Acetaldet.	0	**71**	0	0	**19**
	Acetone	0	2	**73**	0	0
	Ethylene	0	0	**11**	**177**	0
	Ethanol	0	0	0	0	**358**

References

[1] C. Linster, T. Cleland, Glomerular microcircuits in the olfactory bulb, *Neural Network*, 22 (2009) 1169-1173

[2] B. Raman, R. Gutierrez-Osuna, Concentration normalization with a model of gain control in the olfactory bulb. *Sensors and Actuators B: Chemical* 116 (2006) 36–42.

[3] E. Martinelli, D. Polese, F. Dini, R. Paolesse, D. Filippini, I. Lundström, C. Di Natale, An investigation on the role of spike latency in an artificial olfactory system. *Frontiers in neuroengineering* 4: 16. (2011)

[4] A. Gutierrez, S. Marco (editors) *Biologically inspired signal processing for chemical sensors* (2009) Springer Verlag (Berlin, Germany)

[5] D. Schild, H. Reidel, Significance of glomerular compartmentalization for olfactory coding *Biophysical Journal,* 61 (1992) 704-715